JHU CLSP Summer School

Pattern Recognition Applied to Music Signals

1. **Music Content Analysis**
2. **Classification and Features**
3. **Statistical Pattern Recognition**
4. **Gaussian Mixtures and Neural Nets**
5. **Singing Detection**

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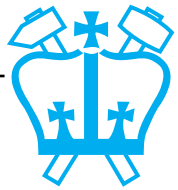
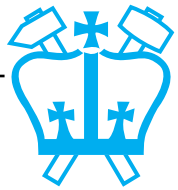
July 1st, 2003



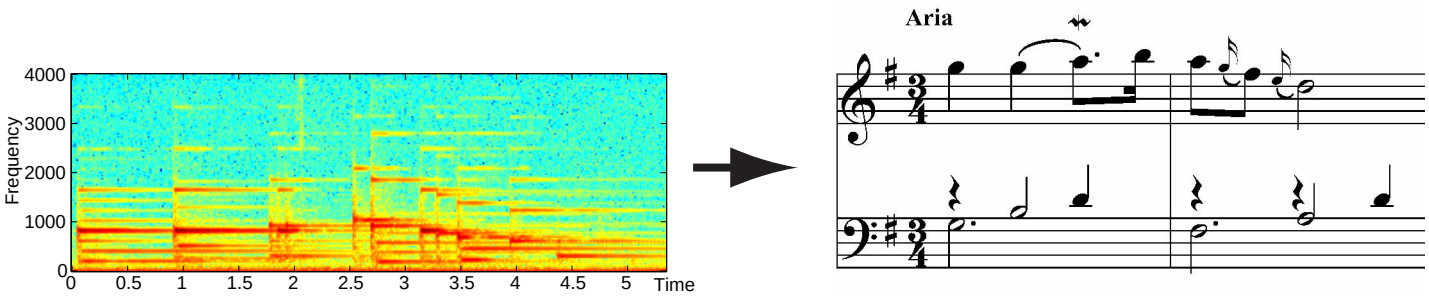
1 Music Content Analysis

- **Music contains information at many levels**
  - what is it?
- **We'd like to get this information out automatically**
  - fine-level transcription of events
  - broad-level classification of pieces
- **Information extraction can be framed as: pattern classification / recognition or machine learning**
  - build systems based on (labeled) training data



Music analysis

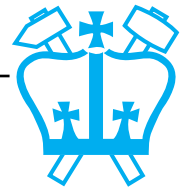
- **What information can we get from music?**



- **Score recovery**
  - extract the 'performance'
- **Instrument identification**
- **Ensemble performance**
  - 'gestalts': chords, tone colors
- **Broader timescales**
  - phrasing & musical structure
  - artist / genre clustering and classification

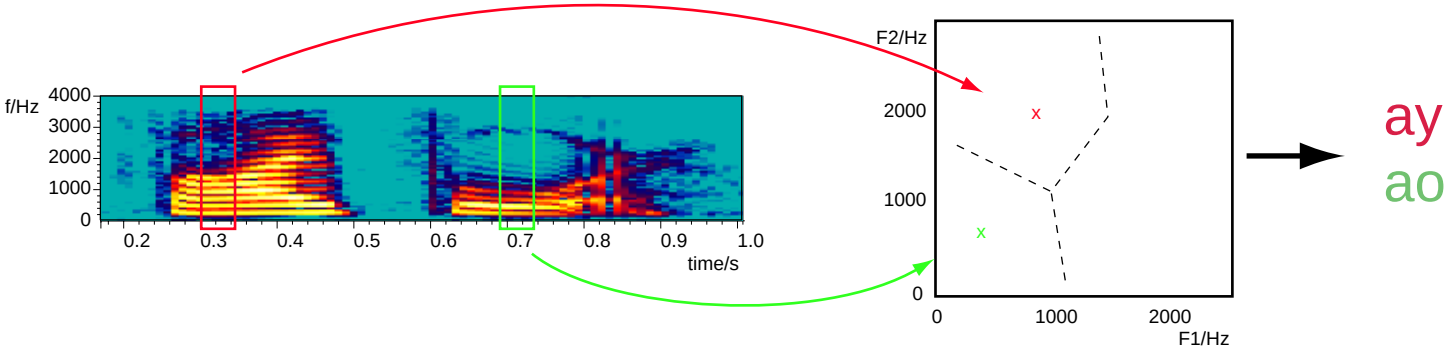
Outline

1. Music Content Analysis
2. **Classification and Features**
   - classification
   - spectrograms
   - cepstra
3. Statistical Pattern Recognition
4. Gaussian Mixtures and Neural Nets
5. Singing Detection

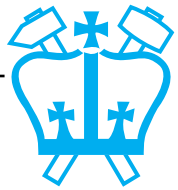


2 Classification and Features

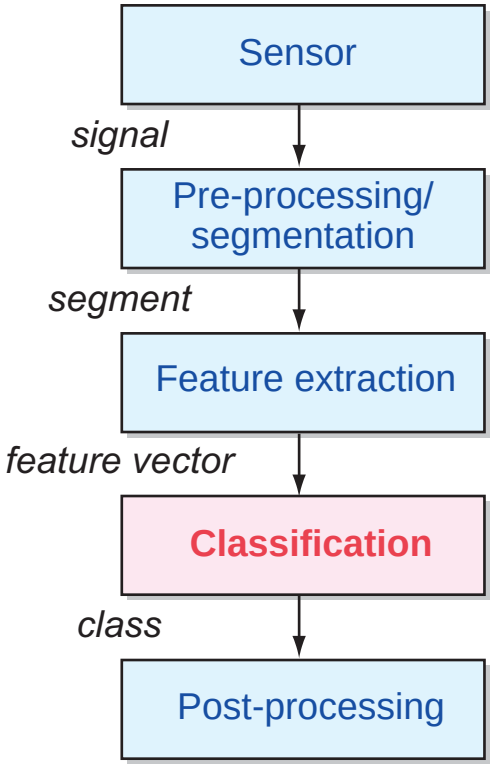
- **Classification means:**
  finding categorical (*discrete*) labels
  for real-world (*continuous*) observations



- **Problems**
  - parameter tuning
  - feature overlap



Classification system parts

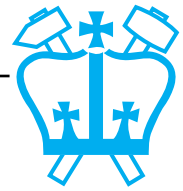


- STFT
- Locate vowels

- Formant extraction

- Context constraints
- Costs/risk

- **Right features are critical**
  - place upper bound on classifier
  - should make important aspects visible
  - invariance under irrelevant modifications

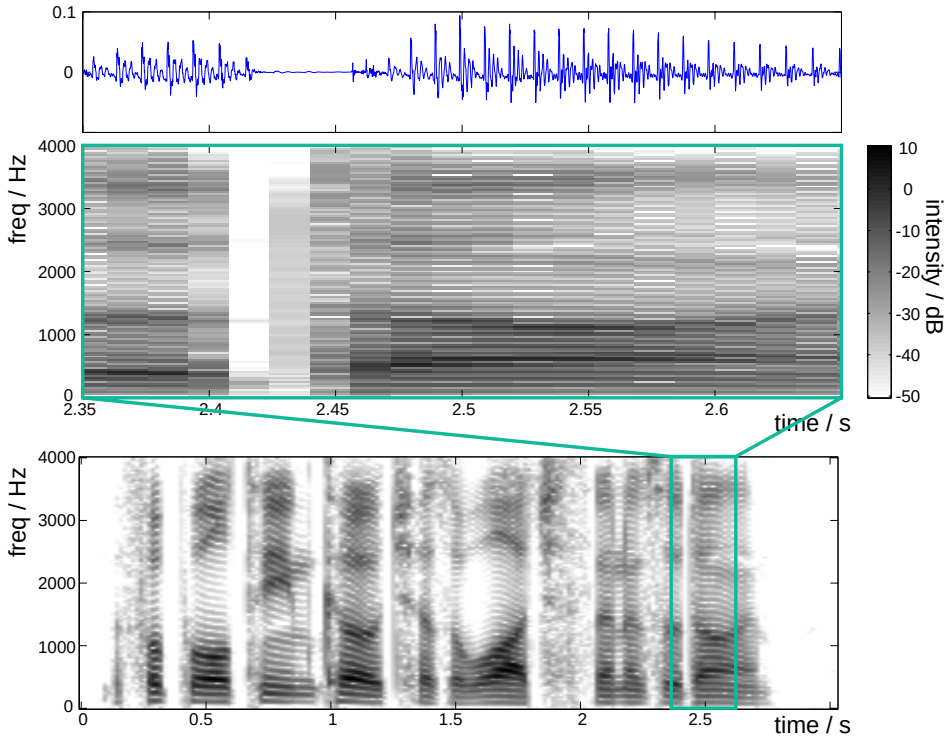


The Spectrogram

- **Short-time Fourier transform:**

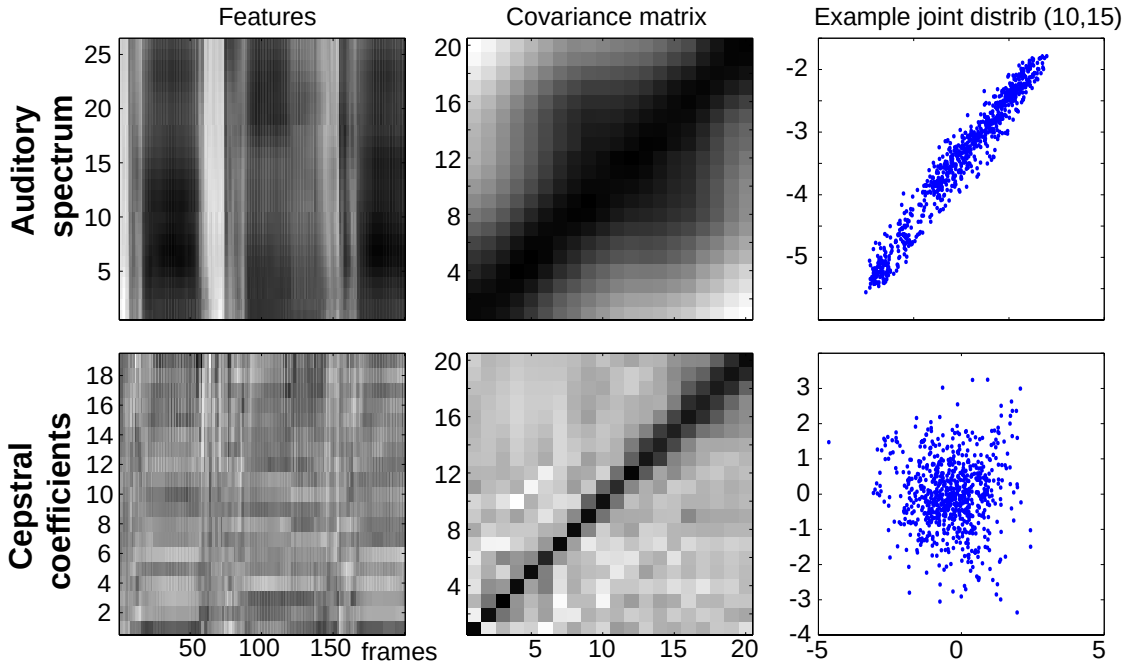
$$X[k,m] = \sum_{n=0}^{N-1} x[n] \cdot w[n-mL] \cdot \exp -j\left(\frac{2\pi k(n-mL)}{N}\right)$$

- **Plot STFT $X[k,m]$ as a grayscale image:**



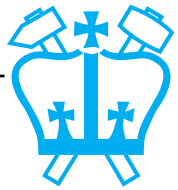
Cepstra

- **Spectrograms are good for visualization; Cepstrum is preferred for classification**
  - dct of STFT: $c_k = \mathrm{idft}(\log|X[k,m]|)$
- **Cepstra capture coarse information in fewer dimensions with less correlation:**



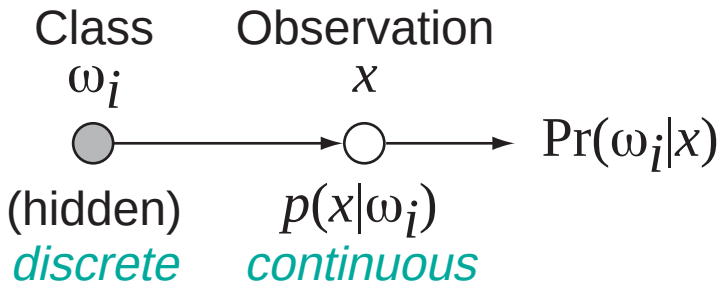
Outline

1. Music Content Analysis
2. Classification and Features
3. **Statistical Pattern Recognition**
   - Priors and posteriors
   - Bayesian classifier
4. Gaussian Mixtures and Neural Nets
5. Singing Detection

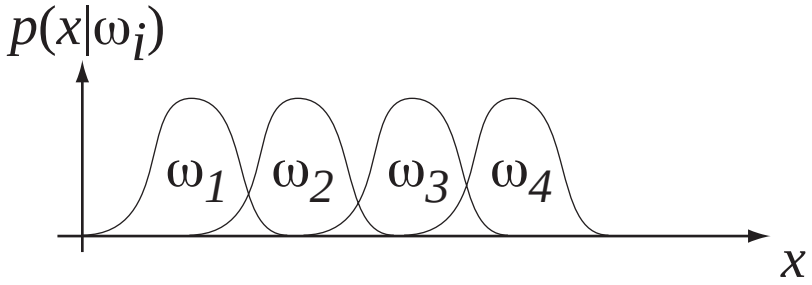


3 Statistical Pattern Recognition

- **Observations are random variables whose distribution depends on the class:**



- **Source distributions** $p(x|\omega_i)$
  - reflect variability in feature
  - reflect noise in observation
  - generally have to be estimated from data (rather than known in advance)



Priors and posteriors

- **Bayesian inference can be interpreted as updating prior beliefs with new information, x:**

Bayes' Rule:

Likelihood

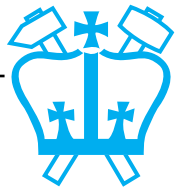
$$Pr(\omega_i) \cdot \frac{p(x|\omega_i)}{\sum_j p(x|\omega_j) \cdot Pr(\omega_j)} = Pr(\omega_i|x)$$

Prior probability

'Evidence' = p(x)

Posterior probability

- **Posterior is prior scaled by likelihood & normalized by evidence (so Σ(posteriors) = 1)**
- **Objection: priors are often unknown**
  - but omitting them amounts to assuming they are all equal

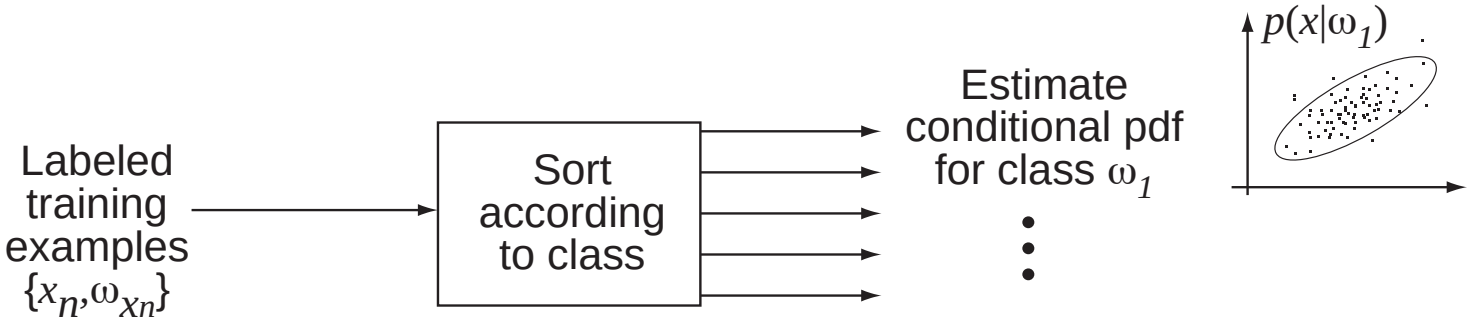


Bayesian (MAP) classifier

- **Optimal classifier is** $\hat{\omega} = \underset{\omega_i}{\operatorname{argmax}}\, Pr(\omega_i|x)$

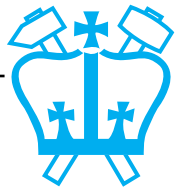
  but we don't know $Pr(\omega_i|x)$

- **Can model conditional distributions** $p(x|\omega_i)$ **then use Bayes' rule to find MAP class**



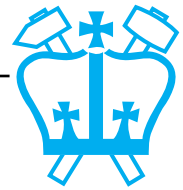
- **Or, can model directly e.g. train a neural net to map from inputs** x **to a set of outputs** $Pr(\omega_i)$

  - discriminative model



Outline

1. Music Content Analysis
2. Classification and Features
3. Statistical Pattern Recognition
4. **Gaussian Mixtures and Neural Nets**
   - Gaussians
   - Gaussian mixtures
   - Multi-layer perceptrons (MLPs)
   - Training and test data
5. Singing Detection

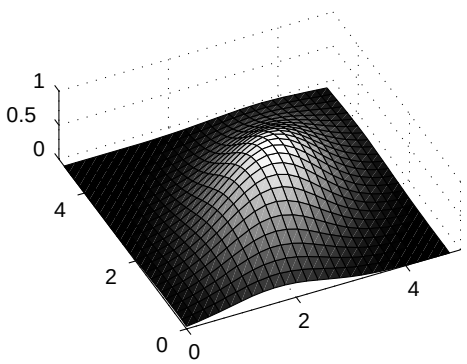


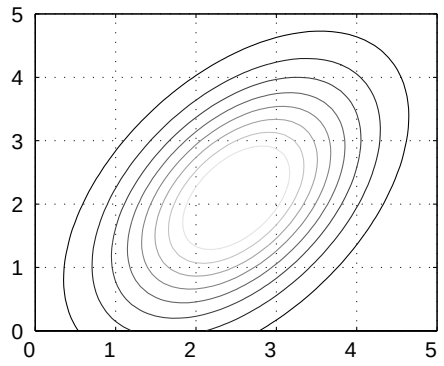
4 Gaussian Mixtures and Neural Nets

- **Gaussians as parametric distribution models:**

$$p(\mathbf{x}|\omega_i) = \frac{1}{(\sqrt{2\pi})^d |\Sigma_i|^{1/2}} \cdot \exp\left[-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^T \Sigma_i^{-1}(\mathbf{x}-\mu_i)\right]$$

- **Described by d dimensional mean vector μ_i and d x d covariance matrix Σ_i**





- **Classify by maximizing log likelihood i.e.**

$$\underset{\omega_i}{\text{argmax}} \left[-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^T \Sigma_i^{-1}(\mathbf{x}-\mu_i) - \frac{1}{2}\log|\Sigma_i| + \log Pr(\omega_i)\right]$$

Gaussian Mixture models (GMMs)

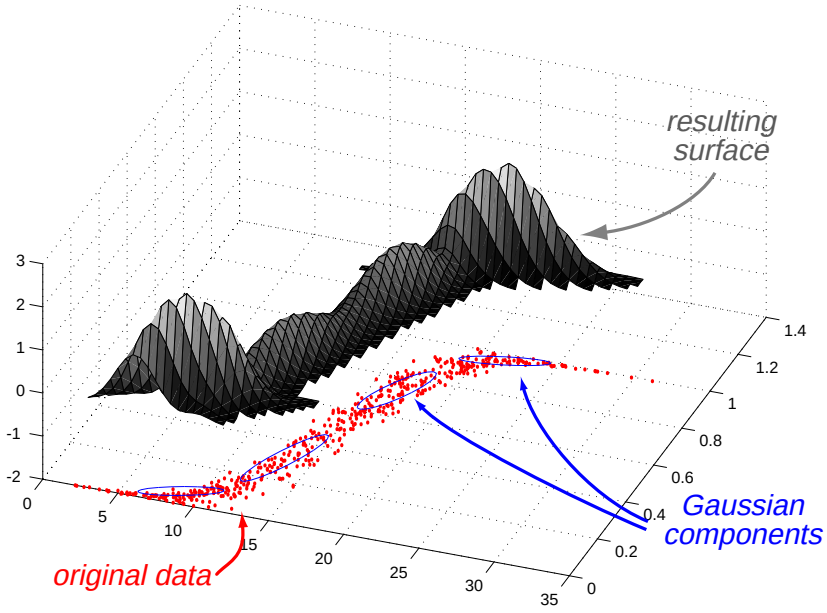
- **Weighted sum of Gaussians can fit any PDF:**

  i.e. $p(x) \approx \sum_k c_k p(x|m_k)$

  weights c_k

  Gaussians $p(x|m_k)$

  - each observation from random single Gaussian?

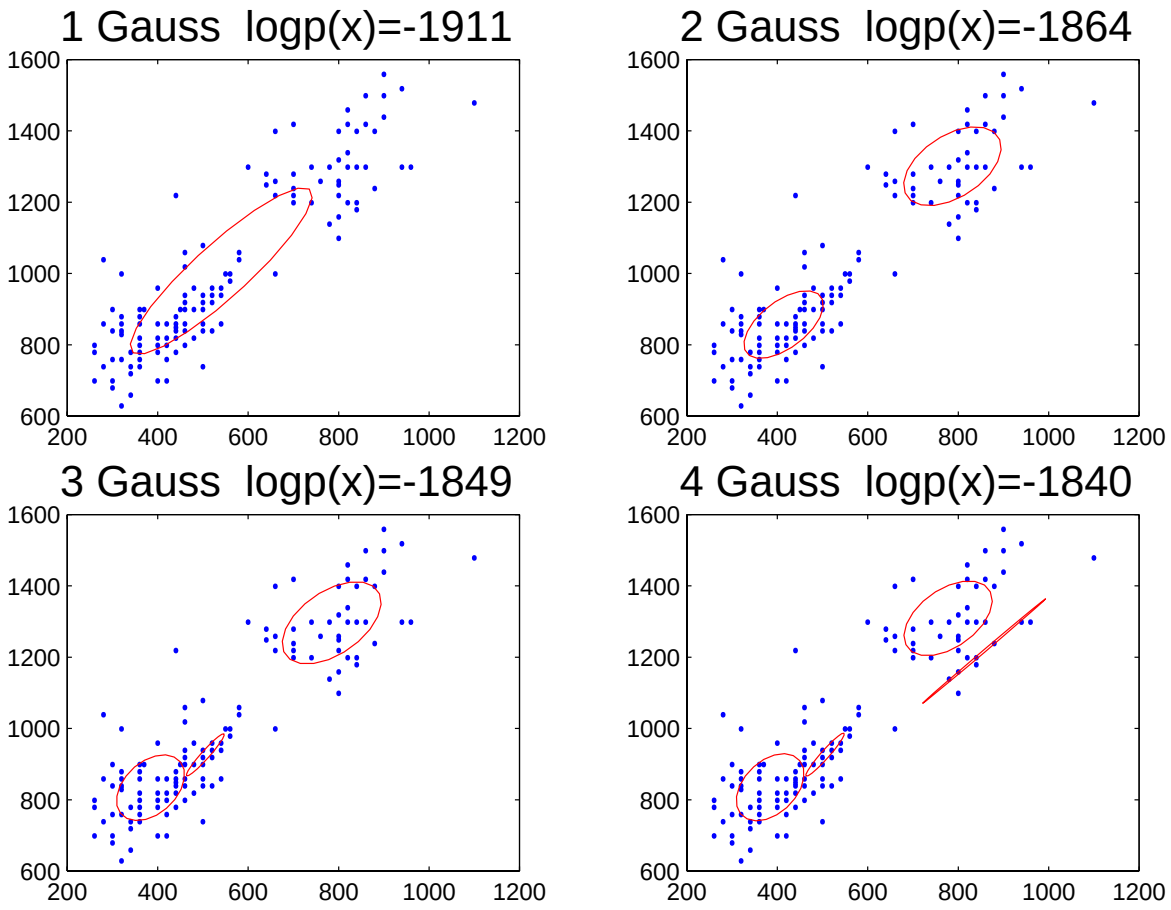


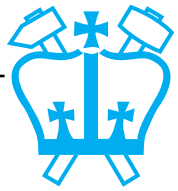
- **Find c_k and m_k parameters via EM**

  - easy if we knew *which* m_k generated each x

GMM examples

- **Vowel data fit with different mixture counts:**

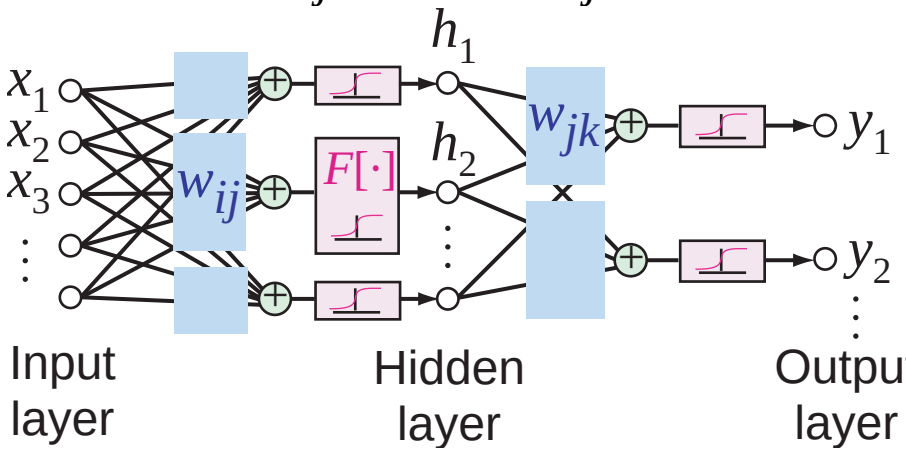




Neural networks

- **Don't model distributions** $p(x|\omega_i)$ **,**
  instead, model posteriors $Pr(\omega_i|x)$
- **Sums over nonlinear functions of sums**
  → large range of decision surfaces
- **e.g. Multi-layer perceptron (MLP)**
  with 1 hidden layer:

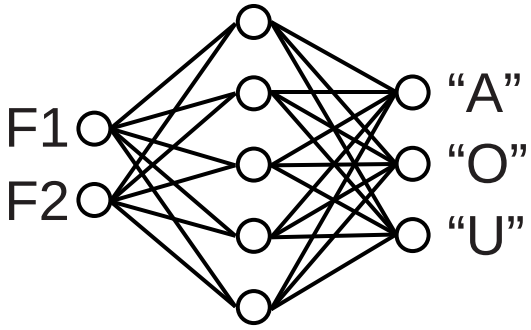
$$y_k = F[\sum_j w_{jk} \cdot F[\sum_j w_{ij} x_i]]$$



- **Train the weights** w_{ij} **with back-propagation**

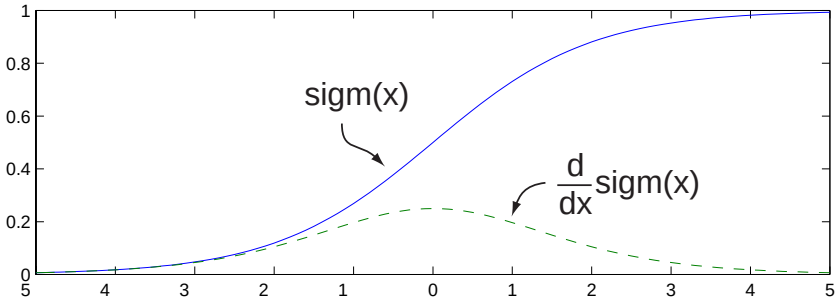
Neural net example

- **2 input units (normalized F1, F2)**
- **5 hidden units, 3 output units (“U”, “O”, “A”)**

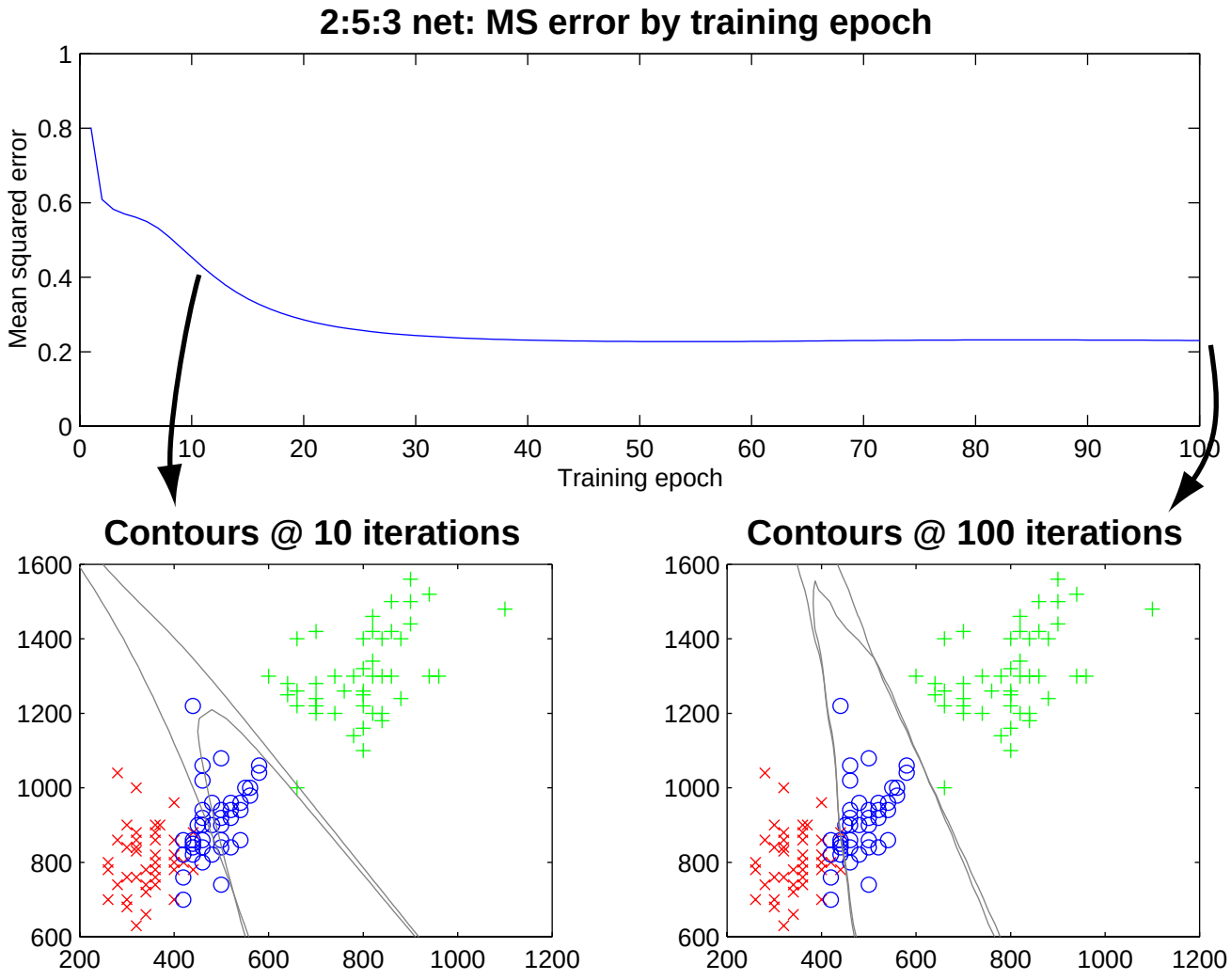


- **Sigmoid nonlinearity:**

$$F[x] = \frac{1}{1+e^{-x}} \quad \Rightarrow \quad \frac{dF}{dx} = F(1-F)$$



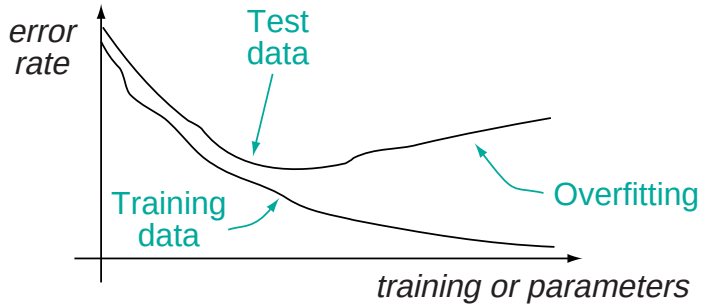
Neural net training



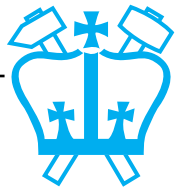
example...

Aside: Training and test data

- **A rich model can learn *every* training example (*overtraining*)**

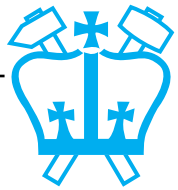


- **But, goal is to classify new, unseen data i.e. *generalization***
  - sometimes use 'cross validation' set to decide when to stop training
- **For evaluation results to be meaningful:**
  - don't test with training data!
  - don't *train* on *test* data (even indirectly...)



Outline

1. Music Content Analysis
2. Classification and Features
3. Statistical Pattern Recognition
4. Gaussian Mixtures and Neural Nets
5. **Singing Detection**
   - Motivation
   - Features
   - Classifiers

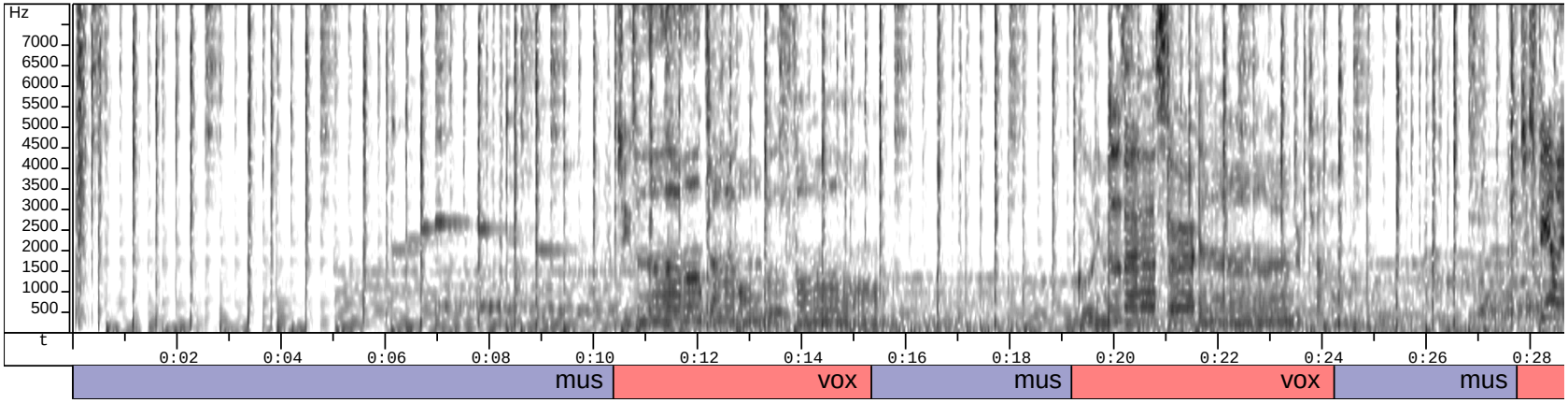


5 Singing Detection

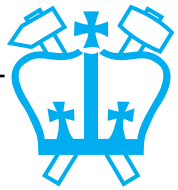
(Berenzweig et al. ’01)

- **Can we automatically detect when singing is present?**

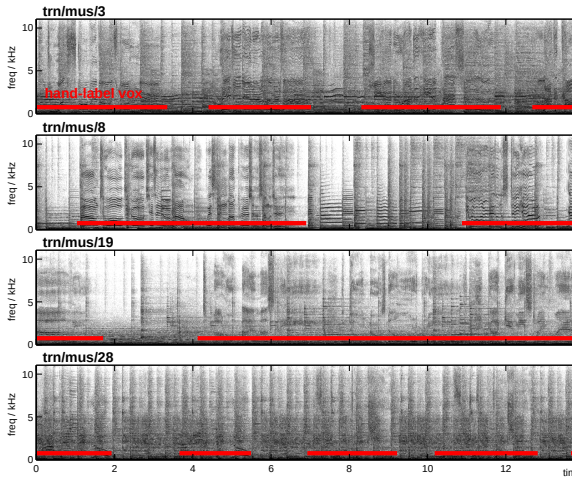
File: /Users/dpwe/projects/aclass/aimee.wav



- for further processing (lyrics recognition?)
- as a song signature?
- as a basis for classification?



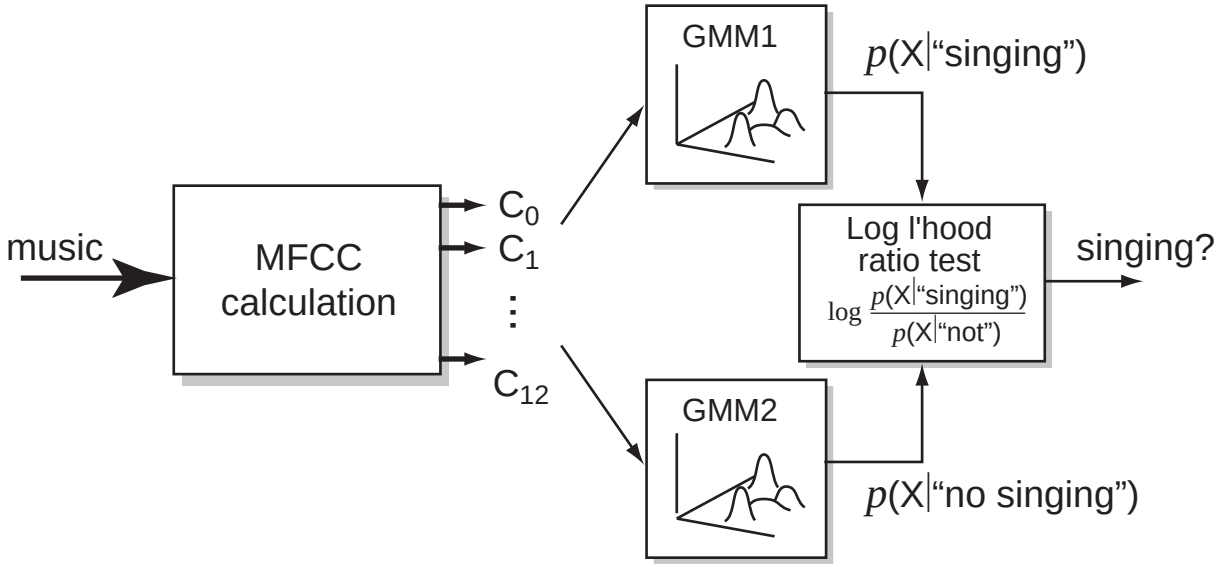
Singing Detection: Requirements



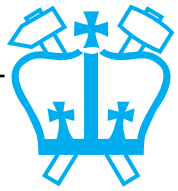
- **Labeled training examples**
  - 60 x 15 sec. radio excerpts
  - hand-mark sung phrases
- **Labeled test data**
  - several complete tracks from CDs, hand-labelled
- **Feature choice**
  - Mel-frequency Cepstral Coefficients (MFCCs) popular for speech; maybe sung voice too?
  - separation of voices? temporal dimension?
- **Classifier choice**
  - MLP Neural Net
  - GMMs for singing / music
  - SVM?

GMM System

- **Separate models for** $p(x|sing)$**,** $p(x|no\ sing)$
  - combined via likelihood ratio test

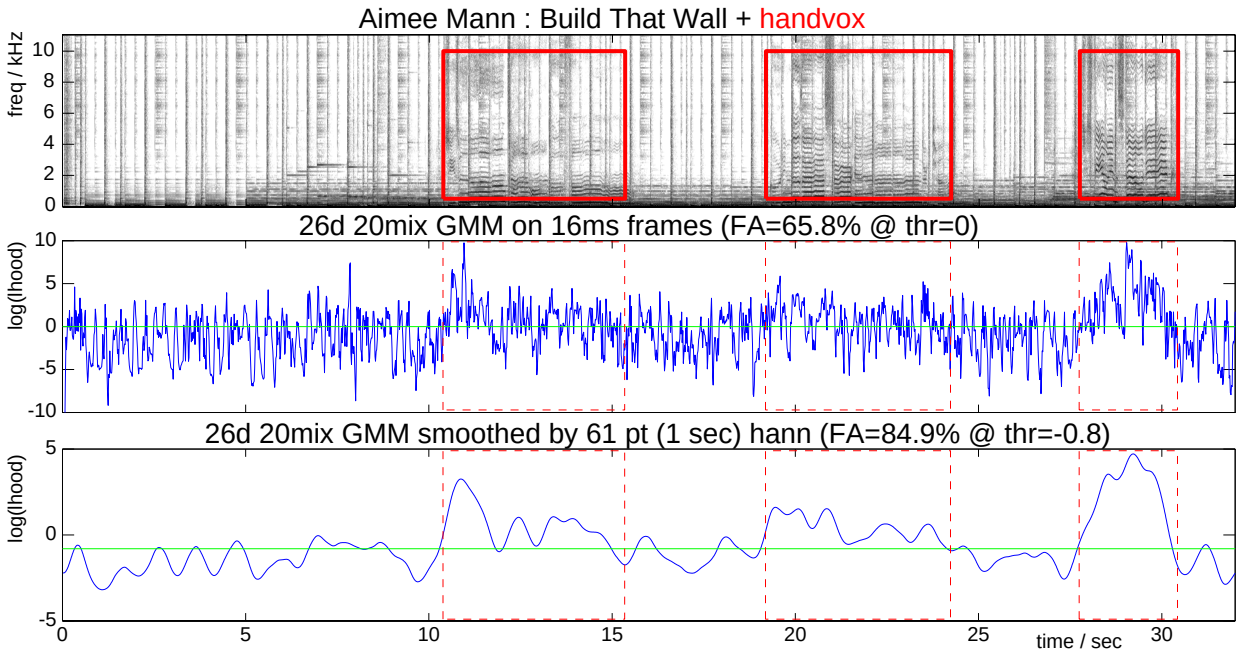


- **How many Gaussians for each?**
  - say 20; depends on data & complexity
- **What kind of covariance?**
  - diagonal (spherical?)

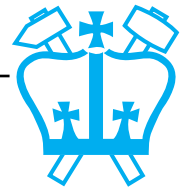


GMM Results

- **Raw and smoothed results (Best FA=84.9%):**

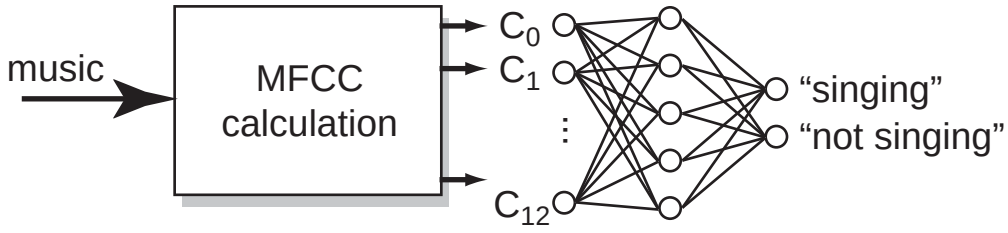


- **MLP has advantage of discriminant training**
- **Each GMM trains only on data subset**
  → faster to train? (2 x 10 min vs. 20 min)

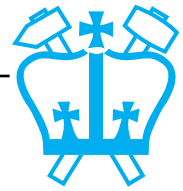


MLP Neural Net

- **Directly estimate** $p(\text{singing} \mid x)$

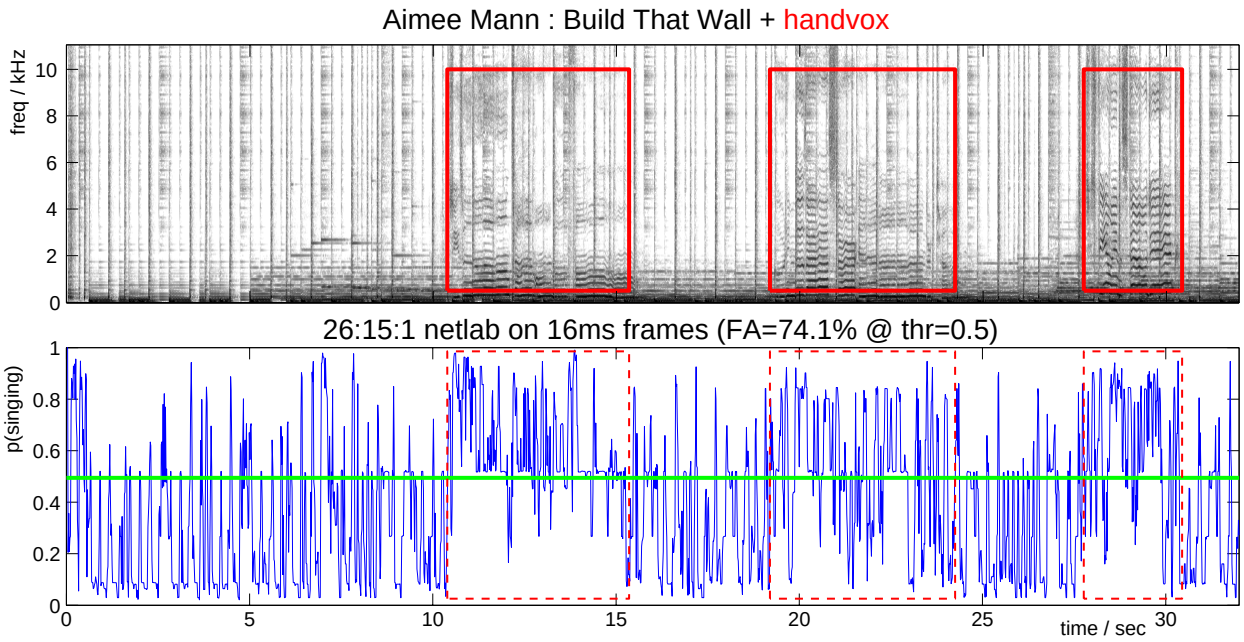


  - net has 26 inputs (+Δ), 15 HUs, 2 o/ps (26:15:2)
- **How many hidden units?**
  - depends on data amount, boundary complexity
- **Feature context window?**
  - useful in speech
- **Delta features?**
  - useful in speech
- **Training parameters...**

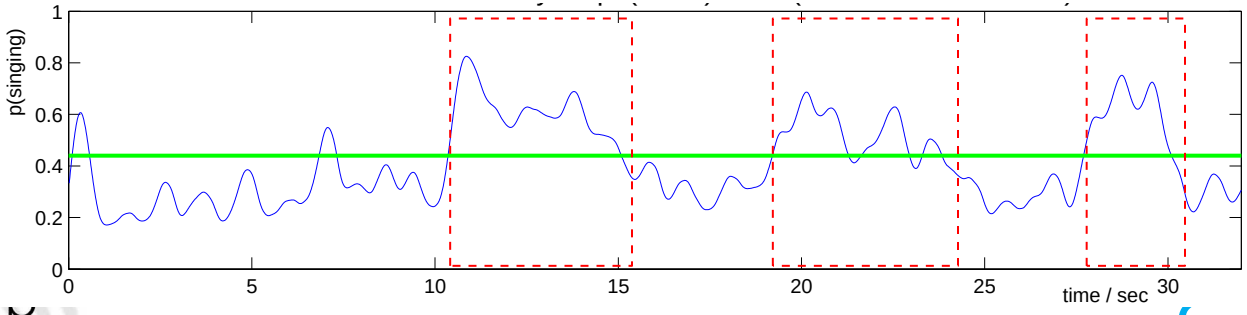


MLP Results

- **Raw net outputs on a CD track (FA 74.1%):**



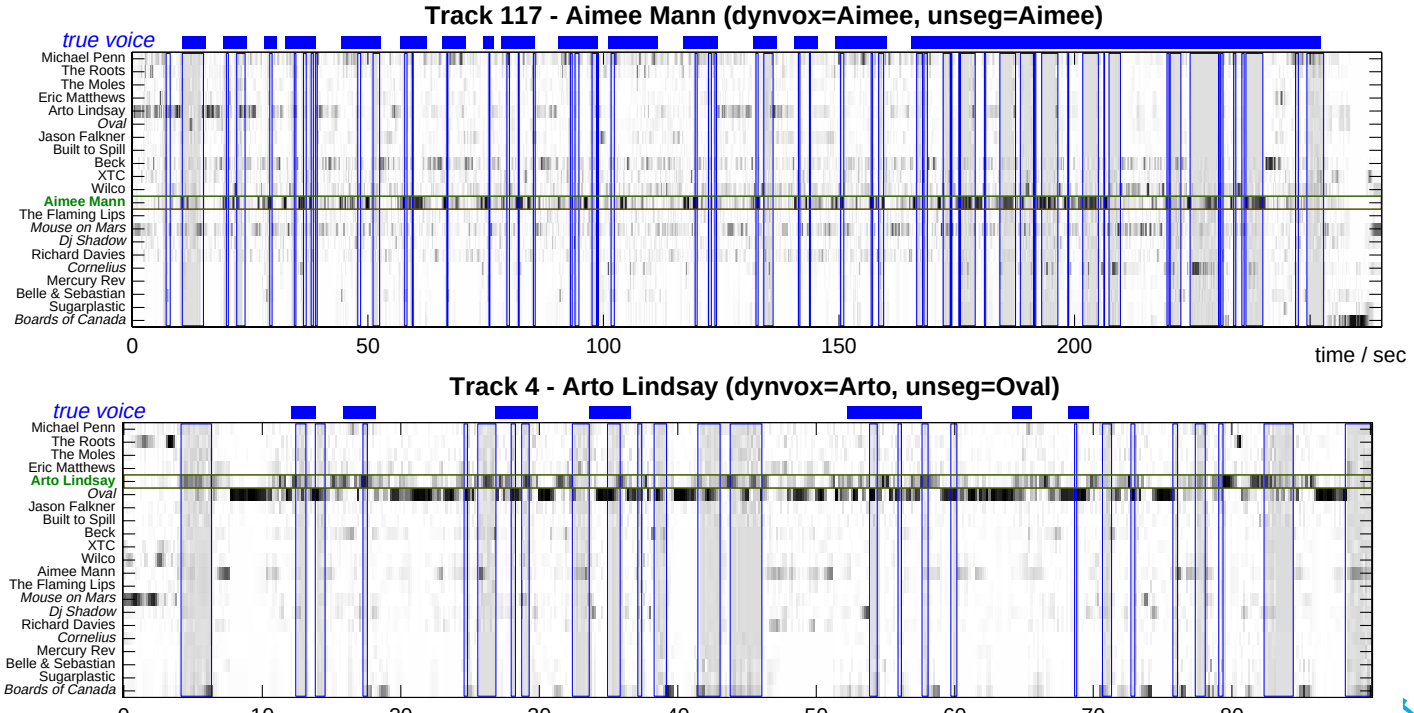
- **Smoothed for continuity: best FA = 90.5%**



Artist Classification

(Berenzweig et al. 2002)

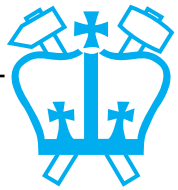
- **Artist label as available stand-in for genre**
- **Train MLP to classify frames among 21 artists**
- **Using only "voice" segments:**
  Song-level accuracy improves 56.7% → 64.9%



Summary

- **Music content analysis: Pattern classification**
- **Basic machine learning methods: Neural Nets, GMMs**
- **Singing detection: classic application**

but... the time dimension?



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